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Simulation of extreme storm effects on regional forest soil carbon stock

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ABSTRACT

This study aims to project changes in soil carbon stocks under different frequencies of storm and climate change scenarios. We calibrated and validated the dynamic process-based soil carbon model “Yasso07” for a wind-throw prone forest area of 1.4 M ha in the State of Baden Württemberg in central Europe, Germany. We fitted climate-biomass models using retrospective climate data and biomass measurements from three consecutive national forest inventories for six forest growth regions. Three IPCC scenarios (RCP2.6, RCP6.0 and RCP8.5), three storm frequencies (10, 20, and 50 years interval), and three post-storm harvest strategies (business-as-usual, full retention, and 50% retention), in combination with a total of 27 scenarios, were applied for projections into the 21st century. We could reduce the uncertainty of YassoBW parameter values significantly by up to 30%, by applying Bayesian calibration, although the absolute value of most parameters did not deviate very much from the original Yasso07 parameters. The projection results showed that forest soil organic carbon (SOC) may lose approximately 30 and 10 t C/ha during the first and the second half of this century, respectively. Three storm frequencies led to a larger range of annual SOC reduction (-0.34, -0.49) t C/ha than climate and harvest strategies (-0.41, -0.42) t C/ha. If no storms occur, the total carbon stock would increase to over 200 t/ha with 258 t/ha under RCP8.5. Considering storm impacts, total forest carbon was reduced from -20 to -90 t C/ha, regarding 10 and 50 year storm frequencies respectively. The largest reduction of forest soil carbon stock originated from the loss in non-solubles (N), followed by acid-solubles (A), humus (H), water-solubles (W) and ethanol-solubles (E).

1. Introduction

Forests have recently drawn much attention from the international community, since their potential function as a carbon sink was recognized under the Kyoto Protocol framework by the UNFCCC (UNFCCC, 1998). Forests in the northern hemisphere are a carbon sink, since the increment was higher than carbon losses due to harvest and mortality (Goodale et al., 2002). At global level, forests might become a carbon source or sink in 2100, according to different model predictions under changing climate (Bellassen and Luyssaert, 2014; Friedlingstein et al., 2006). Such a large-scale finding has to be validated on a regional level, though the quantification of forest carbon sinks is usually associated with a high degree of uncertainty, due to differing methods or incomplete assessment of carbon pools (Houghton et al., 2012). Many researchers have explored the importance of forest ecosystems in the global terrestrial carbon pool and reported that more than 80% of all terrestrial above ground carbon and more than 70% of all soil organic carbon (SOC) are stored in forest ecosystems (Jobbagy and Jackson, 2000). Moreover, according to the 4th IPCC report in 2007, carbon dioxide emissions from the decomposition of soil organic carbon are equal to about 60 Pg (1 Pg $= 10^{15}$ g) of carbon per year, about seven times as much as the annual emissions of fossil carbon (IPCC, 2007). The SOC, consisting of labile compounds and more stable ones, e.g. humus, is the largest terrestrial carbon stock. Globally, SOC is estimated to be 2300 Pg in the top 3 m of mineral soil, almost half (1100 Pg) of which is stored in forest soils (Jobbagy and Jackson, 2000). In these calculations, carbon from forest biomass is not even included, meaning that forest soils alone hold one third more carbon than the atmospheric carbon stock (˜800 Pg), as reported by Houghton et al. (2012).

Furthermore, extreme storm events like Vivian & Wiebke 1990, Lothar 1999, Gudrun 2005, Kyrill 2007 and Klaus 2009 have recently hit European landscapes with a severe impact on forest carbon sequestration capacity (Gardiner et al., 2011). The direct effect was the sharp and sudden reduction in above ground biomass carbon and at a later stage on the assimilation capacity. The influence of storms on forest carbon storage has drawn great attention recently at both national (McNulty, 2002; Thürig et al., 2005) and international level (Schelhaas et al., 2007; Seidl et al., 2014; Reyer et al., 2017). At the EU level including 30 countries (EU and Albania, Bosnia Hercegovina, The FYR of Macedonia, Norway, Switzerland, Turkey, United Kingdom, and

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Yugoslavia), wind-throw was found to be responsible for more than 50% of the primary damage by volume from all biotic and abiotic disturbance events (Schelhaas et al., 2003).

As storms can have a significant impact on forest management, researchers are developing models to predict storm probability and amount of damage to support decision making and mitigate storms' catastrophic effects on forests, e.g. ForestGALES (Gardiner et al., 2011), HWIND (Peltola et al., 1999), WINDA (Blennow and Sallnäs, 2004), FORGEM-W (Schelhaas et al., 2003). Some models are used for modelling damage at the single tree level (Schmidt et al., 2010), while others are used for stand level projections (Hanewinkel et al., 2014) or regional level assessment (Talkkaria et al., 2000). To analyze the impact of storm damage on forest carbon, understanding the carbon processes in forest including forest soil carbon is crucial. Storms not only remove living biomass (in situ carbon sequestration) from forest and affects forest production process (production machine tree is damaged) but also expose forest soil to direct sunshine and affect the evapotranspiration process. Immediate increase in litter input to soil after storms affect forest soil processes including organic and inorganic carbon stock. These models, however, are calibrated for a specific region and are accordingly valid under certain conditions. These models can be simply re-applied to other regions, as long as the empirical data are available, making the comparison between observed damages and model outputs possible by appropriate adjustment or calibration of that model. Yasso, for example, is a complex process-based model, widely used for forest soil carbon analysis (Liski et al., 2005, 2008). It covers the most important aspects of soil organic matter decomposition and mass flow among different carbon compartments, while requiring relatively simple information on litter input and basic climatic data to run the model. The new Yasso07 model (Tuomi et al., 2008, 2009) uses four labile compartments: acid-solubles, water-solubles, ethanol-solubles and non-solubles (A-W-E-N) and one recalcitrant humus compartment (A-W-E-N-H-*N*-).

Forest models are normally designed and developed based on observations or experiments under specific environmental conditions within a specific geographical boundary. The application of models to other domains outside their original area without any modification or re-calibration can cause inaccuracy and uncertainty (Reyer et al., 2010). In this regard, the use of advanced mathematical methods, e.g. Bayesian approaches, has undergone a rapid development in recent years, as Bayesian calibration (BC) can improve a model by updating parameters and reducing uncertainties and thus enhancing model applicability and reliability (van Oijen et al., 2005, 2013). BC approaches are recently applied to studies on soil organic matter decomposition models, carbon turnovers in forest soils, water and heat fluxes in forest stands, as well as forest soil acidification models (Xenakis et al., 2008). A new trend of applying BC to forest process models, is the integration of other types of data sources, such as remote sensing data sets. A UK study to simulate the growth of UK Corsican pine has taken a lead in this aspect (Patenaude et al., 2008). General conclusions from the above mentioned studies show that BC provides a good method for improving the applicability, effectiveness and functionality of forest models by reducing model uncertainty, parameter uncertainty and interaction, as well as model comparison. Therefore, we apply BC for calibrating Yasso07 for the state of Baden Württemberg (BW) and named it "YassoBW". We chose this region because central Europe is one of the hotspots in terms of storm damage to forests and the growing stock in southwestern Germany has been severely damaged (in excess of tens of millions m^3) during the last three decades (Rottmann, 1986; Kühnel, 1994; Kronauer, 2000; Hanewinkel et al., 2014). The most remarkable winter storm in southwest Germany was Lothar 1999, which caused about 50.3 million m^3 of damaged timber over bark, accounting for up to 10% of the total growing stock in the state of BW, according to the second National Forest Inventory (NFI2) (Kändler et al., 2005).

There are a few studies that provided a quantitative analysis on how forest carbon budgets are affected by storm events at the national and transnational level (McNulty, 2002; Thürig et al., 2005). However, such a study is lacking for the highly productive forests of southwest Germany damaged by several large storm events in the last 25 years (e.g. Vivian/Wiebke in 1990 and Lothar in 1999). Similar storm events are expected to occur in 21st century and their frequency and severity may change substantially (Schelhaas et al., 2007; Seidl et al., 2014; Reyer et al., 2017). Therefore, it is of great interest for forest managers and decision makers to know, how the carbon stocks (including the forest soils) will be affected under various combinations of storm and climate scenarios. Accordingly, the overall objective of this study is to quantify the influence of extreme storm events on the forest carbon storage capacity in BW (Southwest Germany) under different climate scenarios.

The specific research questions of this study are i) How can a process-based soil carbon model be calibrated to the local conditions using an advanced Bayesian approach and detailed local information? ii) How and to what extent will forest biomass and carbon budget be affected by combined impacts of storm and climate scenarios? iii) How various storm frequencies, different post-storm harvest strategies, and climate change scenarios may affect forest soil carbon? In the following, we draw attentions to advanced modelling approaches of this study and the outcomes about forest soil carbon pools and its sensitivity to future climate, storms, and management interventions. Accordingly we formulate three main hypotheses as following:

1) Bayesian calibration can reduce original models parameters uncertainty using extensive regional data
2) Extreme wind storms have significant impacts on forest soil carbon budget
3) Post-storm management of damaged forest areas has implications for future forest soil carbon development

2. Materials and methods

2.1. Study region and forest inventories

According to the third National Forest Inventory (NFI3) in 2012, the study region in southwest Germany (the federal state of BW) has a total stocked forest area of 1.32 million hectares and the forest area covers 38.4% of the total land area (Fig. 1). Based on the variation in bioclimatic characteristics and site conditions, this region is divided into seven growth regions (Fig. 1). For the sake of comparison and better representativeness, the biomass projection and litter input as well as carbon stock predictions are carried out for each region individually. The dominating tree species in BW are Norway spruce (*Picea abies*) and European beech (*Fagus sylvatica*), which cover 34% and 21.8% of the total forest area, respectively. The standing volume per hectare reaches 378 m^3/ha, which is almost three times the average growing stock of European forests (137 m^3/ha), making the forest area in BW one of the less harvested regions in Europe. However, the annual increment slowed down slightly from 1.5 million m^3, between NFI1 - NFI2 (1987–2002), to 1.4 million m^3, between NFI2 - NFI3 (2002–2012) as a sign of carbon sink saturation in European forest biomass (Nabuurs et al., 2013).

2.2. Forest inventory, soil, and weather data

We use the results of the National Forest Soil Inventory (NFSI) representing the average forest soil types and species distribution within the entire forest area of BW. The sample plots in the study region are distributed on 8 × 8 km grids in forested areas and the mineral soil samples were taken from the layers 0–5 cm, 5–10 cm, 10–20 cm, 20–30 cm, 30–60 cm, 60–90 cm, 90–140 cm and 140–200 cm, or to the lowest depth until bedrock is reached (BMELV, 2007). The first National Forest Soil Inventory (NFSI1) was started in 1989 and ended in 1992, while the second National Forest Soil Inventory (NFSI2) was

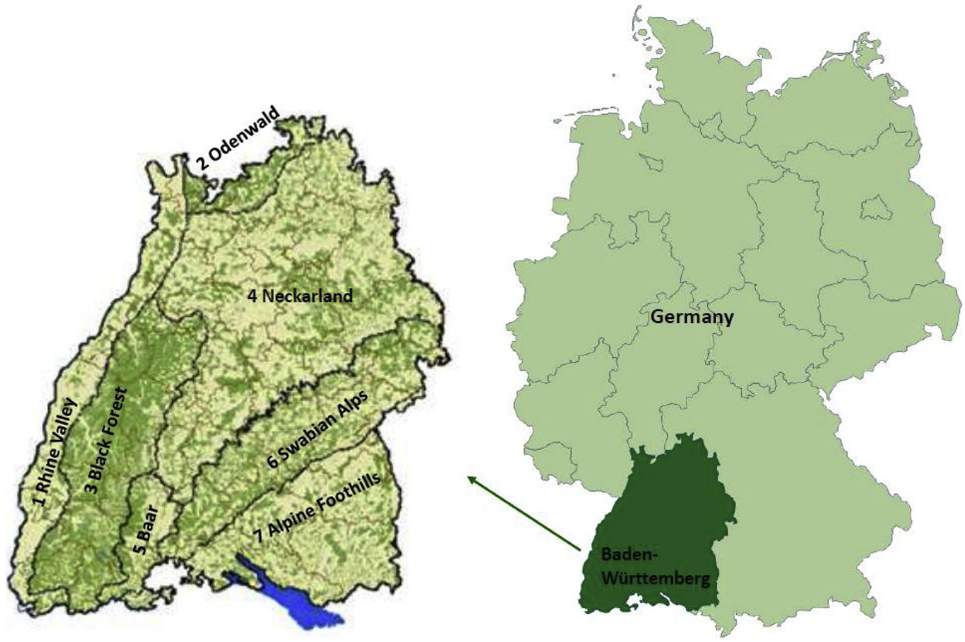

Fig. 1. Main forest growth regions in Baden Württemberg (BW) based on bio-climatic and site conditions. Dark green applies for forest areas. Source: adapted from Waldzustandsbericht 2011 (FVA, 2011) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

completed between 2006 and 2008 at the same sampling sites with a one or two meters shift from the digging point of the first survey depending on the real physical condition of that specific site. In general, the NFSI provides valuable data on various topics related to forest and soil sciences including, among others, forest condition, soil property changes between NFSI1 and NFSI2, soil carbon, biodiversity and influence of climate change on soil conditions (see more details in Supplementary).

For the sake of consistency between two soil surveys, four selection criteria were applied to choose the sampling sites from the 280 remeasured plots. Firstly, whether soil type (Sand, Clay, Loam, Silt, and Peaty) and horizons (from humus to mineral soils and including measured horizons L, Of, Oh, Ah, B, C, R) were the same. Secondly, if the difference in stone content was not higher than two times the standard deviation (approximately 25% difference). Thirdly, whether the forest stand types agree (conifer-deciduous mixed stands). Fourthly, both NFSI1 and NFSI2 had an apparent humus horizon. As long as one of the above mentioned criteria was not met, that site was excluded from further analysis. This resulted in 183 sampling plots (excluding 97 sites) that satisfied all these criteria and meanwhile had humus measurement at both soil surveys. The SOC in these 183 sampling sites, including humus horizon and mineral soil down to 60 cm, showcased a similarly declining trend in the 280 plots. SOC was reduced in the model using validation samples from 100.3 t/ha in NFSI1 to 91.3 t/ha in BEZ2 in mean value of the 183 sites (compare to 108.0 and 89.8 t/ha in NFSI1 and NFSI2, respectively).

The retrospective climate data were derived from the German Meteorological Service (DWD) database. Since the climate data have the downscaled resolution of 1 km and NFSI sites data resolution is 8 km, the value of the specific climatic data square (1 km * 1 km), within which a NFSI site was located, was assigned to that specific NFSI site (see more details in Supplementary). According to the temporal resolution of our modelling framework, the temperature values were derived from the daily mean air temperature at German Meteorological Service (DWD) station and used to calculate the monthly and annual mean temperatures. Annual precipitation was aggregated for each year and each NFSI site. Fig. 2 shows the historical climate data averaged geographically over all soil survey sites for the time period of 1989–2008. The twenty year climate data were used because they covered the time period in which NFSI1 and NFSI2 were conducted. Temperature amplitude was defined as the difference between the maximum monthly mean temperature and minimum monthly mean temperature in one year divided by two. During 1989–2008, it had a range of almost 5 °C for BW. According to the results of the study by Tuomi et al. (2009), these types of climate patterns and litter quality are the major controlling factors of decomposition rates at the global scale also valid for the model YassoBW.

2.3. IPCC climate scenarios

LUBW and lubw (2012) stated that the first decade of the 21 st century was the warmest in Germany for at least the past 130 years. The mean temperature increase of over 1 °C has been observed in BW (LUBW and lubw, 2012), in comparison to the global rise of about 0.7 °C in the period of 1906–2005 (IPCC, 2007). Climate change projections were normally performed by simulations using Global Climate Models (GCMs). Different GCMs can generate largely different climatic projection data by using different emission scenarios and model runs. Since there is still no downscaled database for the future climate in BW, the WorldClim - Global Climate Data (Hijmans et al., 2014) was used for above ground biomass projection and underground soil decomposition in BW until the end of the 21st century. In order to minimize the uncertainty of a single GCM on the climate data forecast, the model outputs from three representative GCMs were averaged, e.g. CCSM4, HadGEM2-AO and MIROC-ESM. These GCM outputs were downscaled and calibrated (bias corrected) using WorldClim 1.4 as a baseline for the 'current' climate (Hijmans et al., 2014). WorldClim has a repository of 19 bio-climatic variables. We selected annual mean temperature and annual precipitation for this study corresponding temporal resolution of our modelling framework.

For the climate scenarios, we use the most current storylines, i.e., four Representative Concentration Pathways (RCPs) adopted by the fifth IPCC Assessment Report. The four RCPs show four possible greenhouse gas concentration trajectories in the atmosphere until 2100: RCP2.6, RCP4.5, RCP6.0 and RCP8.5. Each of these trajectories represents a potential range of radiative forcing values for the end of the 21 st century (+2.6, +4.5, +6.0 and +8.5 W/m2, respectively) relative to pre-industrial values (IPCC, 2013). Three of the four scenarios

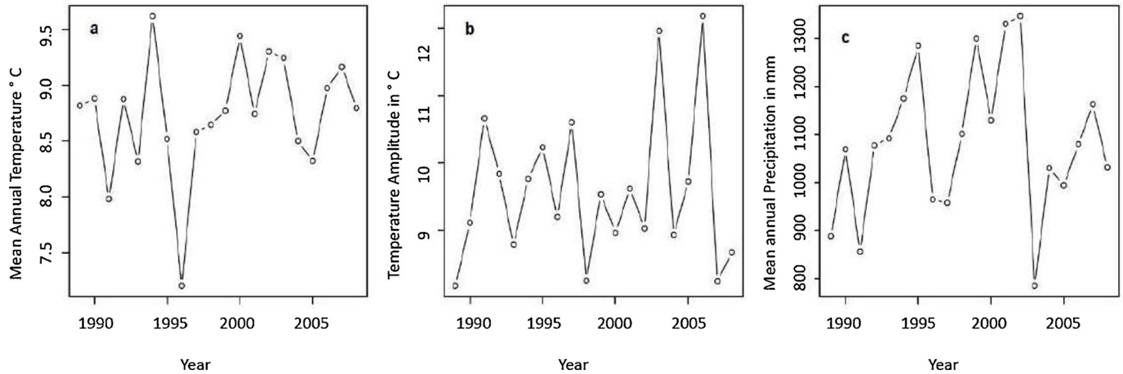

Fig. 2. The annual climate data in 1989–2008 in BW: (a) mean temperature, (b) mean temperature amplitude, (c) annual precipitation.

were chosen for this study, RCP2.6, RCP6.0 and RCP8.5, representing slight, intermediate and substantial changes (Hereafter, named RCP26, RCP60 and RCP85). The outputs from each GCM, combined with each RCP scenario, were clipped for BW in Arc GIS Version 10.0 (ESRI, Environmental Systems Research Institute, Inc., Redlands, California, USA).

2.4. Soil carbon model "Yasso"

The model Yasso, a process-based soil carbon model (Liski et al., 2005), was originally developed for forest soil carbon dynamics analysis with little input requirements. Yasso consists of three labile decomposition compartments (extractives, celluloses, lignin-like compounds) and two relatively stable compartments (active humus and recalcitrant humus). The model simulates forest soil carbon stocks and their changes, as well as carbon release from the soil to the atmosphere at a yearly step. The decomposition rates of the three labile compartments were derived from litter bag experiments in central Sweden (Berg et al., 1991). An updated version, Yasso07, was developed using much larger data sets (Tuomi et al., 2009). For the leaf litter decomposition, nearly 9000 measurements were collected from 72 sites and 32 litter types, covering various ecosystem types in the Northern hemisphere, e.g. tropical rainforest to arctic tundra (Tuomi et al., 2008). The Yasso07 model is composed of five state variables and 24 parameters. The five state variables represent carbon stocks in four labile carbon compartments, e.g. acid-solubles (A), ethanol-solubles (E), water-solubles (W) and non-solubles (N) and one additional compartments for humus (H). The parameter set consists of decomposition rates for each carbon compartment, mass flow proportion among these compartments, climate-dependent variables and size-dependent parameters for woody litter. Yasso07 simulates the carbon cycling in trees, litter and soil organic matter based on a biological process-oriented view of the litter decomposition process. The model assumes that the more stable carbon pools reside in deeper soil layers and, accordingly, does not take into account any carbon stock changes regarding different soil depth. As Yasso07 provides an unbiased estimate of litter decomposition for a wide variety of tree species and forest ecosystems across global climate conditions (Tuomi et al., 2011), applying the Yasso07 model to the forest soils of BW becomes plausible, with the appropriate calibration. Finally and crucially, in Yasso07 each parameter value is given by a probability density function generated by using the Markov Chain Monte Carlo (MCMC) method instead of just the expectation value and its associated variance of the parameter in the previous version of the Yasso model (se details in Supplementary) MCMC is also used to identify which carbon flux exists between different compartments (Liski et al., 2008). The following assumptions are made in using the MCMC method for the calibration of YassoBW (from Yasso07):

- Decomposition rates of the four labile carbon compartments (A-E-W-N) are independent of the origin of litter, e.g. litter types and plant species. They depend rather on favorable air temperature and soil moisture or drought index.
- Decomposition of compounds groups results in the mass loss from the system and mass flow between groups as well as the formation of more recalcitrant humus.
- Mass transfer fractions among compartments are independent of climate.
- Decomposition of woody litter depends additionally on the size of the litter.

In this study, we use Yasso07 designed to minimize the input requirements by using a yearly time step and utilizes the following groups of determinants: 1) environmental and ecological drivers, e.g. air temperature, precipitation, evapotranspiration, photosynthesis, 2) soil condition, e.g. soil temperature, moisture, pH, depth, chemical composition, faunal activity, texture, C/N ratio, 3) vegetation information, e.g. forest growth, litter input quality and quantity, turnover rates, and 4) anthropogenic influence, e.g. forest management, thinning regime, harvest strategy. Many source of data are recruited to run the model properly and generate the demanded outputs. Fig. 3 shows the natural flow of applied dataset in different modelling and analysis steps.

2.4.1. Bayesian calibration of YassoBW

Bayesian Calibration (BC) infers new parameter values of a given model, aiming to quantify and further reduce uncertainty in parameter values. We used BC because, compared to traditional calibration model, it takes into account the range of input instead of an average and allows for learning from new data from observations towards improving model fit. This is achieved by integrating two sources of information: prior knowledge about parameter values and posterior knowledge about measured output data. In our case, the prior information is the prior distribution of Yasso07 parameter values. The measurements on output variables are the soil carbon quantities in A-W-E-N-H compartments. BC

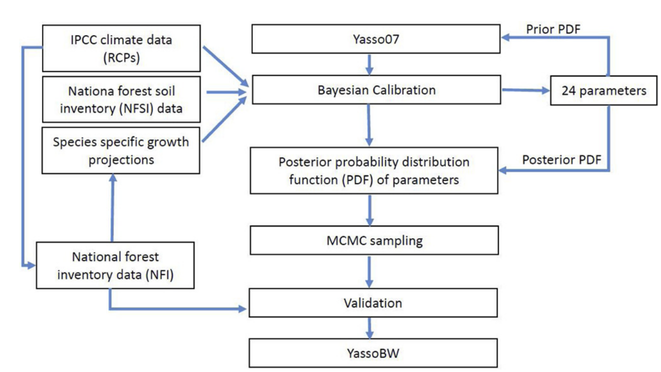

Fig. 3. Flowchart of data flow to analyze forest soil carbon.

can theoretically be applied to models of any type or size (van Oijen et al., 2005, 2013), including statistical models and process-based models, as well as deterministic and stochastic models. The underlying rationale is Bayes' Theorem as in equation 1, where P(θ|D) is the posterior distribution for parameters given the data D, P(θ) is the prior distribution of parameters, P(D|θ) is the likelihood of data given the model output using the parameter θ and P(D) is a normalisation constant.

$$P(\theta|\ D) = P(\theta)^{*}P(D|\ \theta)/P(D) \tag{1}$$

For the sake of commonality and simplicity, a standard Metropolis algorithm is chosen to create a random walk through parameter space. The visited points in the random walk chain constitute a representative sample from a posterior PDF of parameters. Each new point in the chain is found by randomly generating a candidate parameter vector, which can be accepted or rejected (van Oijen, 2008). According to Metropolis et al. (Metropolis et al., 1953), Metropolis algorithm is a tool to determine whether a candidate parameter vector, e.g. a point in the random walk chain, is accepted or not. It depends on the Metropolis ratio (Eq. (2)), which is the ratio of posterior probability of the candidate point to that of the current point. If the Metropolis ratio β is bigger than 1, it means the candidate parameter vector has a higher posterior probability than the current parameter vector, so it is always accepted. If the Metropolis ratio is less than 1, it does not necessarily mean the candidate would be rejected. Conversely, it can also be accepted with the probability equal to the Metropolis ratio (van Oijen, 2008). MCMC is used to estimate all parameter values in Yasso07, e.g. decomposition rate coefficients of AWENH (acid-solubles (A), water solubles (W), Eethanol solubles (E), non-solubles (N), and one recalcitrant humus compartment (H) in YassoBW), transfer fractions between AWENH, climatic dependency parameters of decomposition rates, and transfer fractio is bins to and decomposition of humus as well as woody litter exposure (more details in Supplementary).

$$\beta = \frac{P(\theta^{t+1}|\ D)}{P(\theta^{t}|\ D)} = \frac{P(\theta^{t+1})^{*}P(D|\ \theta^{t+1})}{P(\theta^{t})^{*}P(D|\ \theta^{t})} \tag{2}$$

2.4.2. Data processing for YassoBW

One of the crucial improvements of Yasso07 is that it is not as data intensive as other process-based soil models, e.g. SOILN (Eckersten and Beier, 1998), CENTURY (Parton et al., 1987, 1994) or Forest-DNDC (Li et al., 2000; Stange et al., 2000). To run Yasso07, two sets of input data are needed. The first set is litter input, which contains litter production per year and litter quality, meaning the composition of chemical compounds of A-W-E-N in each tree compartment of different tree species. In the YassoBW model, there are two litter types, woody and non-woody litter. The basis for calculating the litter input were the biomass for the 9549 individual tree measurements obtained from the quasi-NFI inventory (special forest inventory using NFI measurement standards for all soil carbon sampling sites). In this study, the generic biomass functions for European beech (Wutzler et al., 2008) were applied to compute the biomass for tree compartments of roots, stems, branches and leaves for broad-leaved species in BW (Table 1). These compartment proportions were assigned to other deciduous trees, since more than 50% of the deciduous trees were European beech and most deciduous trees compartments realise very similar properties e.g. turnover rate (see below and Table 2).

Forest soil carbon was measured from the litter horizon downwards to the mineral soil, either to a depth of 200 cm or to when bedrock was reached. The soil profile for all measured horizons, e.g., L, Of, Oh, Ah, B, C, R, was examined. The litter input into soil carbon are from living trees, ground (or understory) vegetation, harvest residues and natural mortality (Rantakari et al., 2012). All of these types of litter input were calculated using local data sets from NFI and quasi-NFI inventories, except for the litter input from understory vegetation. For calibration purposes, the understory vegetation, including shrubs, bushes, herbs

Table 1
Best HD-model for each compartment of European beech (Wutzler et al., 2008).

Compartment	Form	Equation
Tree	dh3	$m = 0.0523^{*}d^{2.12}{*}h^{0.655}$
Branch	dh3	$m = 0.123^{*}d^{3.09}{*}h^{-1.17}$
Leaves	dh3	$m = 0.0377^{*}d^{2.43}{*}h^{-0.913}$
Stem	dh2	$m = 0.0293^{*}(d^{2}{*}h)^{0.974}$
Root	d2	$m = 0.0282^{*}d^{2.39}$

[d] is diameter at breast height (1.3 m) in cm and h is tree height in m.
Form of allometric functions applied: $m = c_0 d^{c1}$ (d2), $m = c_0(d^2h)^{c1}$ (dh2), $m = c_0 d^{c1} h^{c2}$ (dh3), where m is the regarded compartment and c0-2 are the coefficients.

Table 2
The turnover rates of tree compartments for the dominant species in Baden Würrtemberg.

Species	Foliage	Branch	Stem Bark	Coarse Root	Fine Root
Spruce	0.14	0.0125	0.0027	0.0125	0.811
Pine	0.33	0.015	0.0052	0.0125	0.868
Fir	0.1	0.04	0.0027	0.0125	0.74
Beech	1	0.0135	0.0029	0.0135	0.868
Oak	1	0.0135	0.0029	0.0135	0.74

and grasses was assumed to provide 0.506 t/ha annually into the soil (Muukkonen and Mäkipää, 2006; Muukkonen et al., 2006), and it was added to the non-woody litter input category. The tree biomass compartments were classified into branches, stems (including bark), foliage and roots. The total above ground biomass of each of the 9549 individual trees was computed using a synthetic biomass function from Kändler and Bösch (2013). The core function of this integrated biomass function (Eq. (3)) is a modified Marklund model for trees greater than 10 cm DBH.

$$B_{AB} = b_0 * e^{b_1 * (DBH/(DBH\ +\ k_1))} * e^{b_2 * (D03/(D03\ +\ k_2))} * H^{b_3} \tag{3}$$

Here B_{AB} is the above ground biomass (kg), DBH is the diameter at breast height (cm), $b_{0,\ 1,\ 2,\ 3,}$ and $k_{1,\ 2}$ are coefficients, D03 is the diameter at 30% of tree height (cm), and H is the tree height (m). The coefficients of the individual biomass functions are documented in the supplementary (s-tables 1–2). The turnover rates, or litter fall, for each tree compartment for different tree species vary significantly as listed in Table 2. According to the NFI statistics, the difference between growing stock under bark and over bark of harvested timber includes not only the bark biomass, but also harvest residues. The ratio of growing stock under bark to over bark was derived from the NFI1 and NFI2 data sets (see details in Supplementary). Estimations on annual removal due to natural mortality were also based on the measurements from the first and second NFI. This parameter contains the volume of standing dead trees and un-used lying dead trees, in terms of growing stock over bark. The litter input from natural mortality was estimated based on the following assumptions: firstly, tree compartment composition, chemical quality (A-W-E-N) and turnover rates from the trees due to natural mortality are the same as living trees. Secondly, beech and oak have their individual mortality rates that are different from all other deciduous species, according to the quasi-NFI database.

Based on the three rates of turnover in Table 2, harvest residue and natural mortality, the litter input estimates (in t/ha) were produced from measurements from the quasi-NFI inventory at the single tree level. Fig. 4a shows that A-W-E-N composition of litter input varies from site to site, but the general trend made it clear that acid-solubles are the most important component, followed by the non-solubles, then water-solubles and finally, ethanol-solubles. As indicated in Fig. 4b, the NWL provided more litter input into soil than the WL at all calibration sites, although the total litter input differed from one site to another. On average, they were estimated at 3.1 t/ha and 0.8 t/ha for NWL and WL,

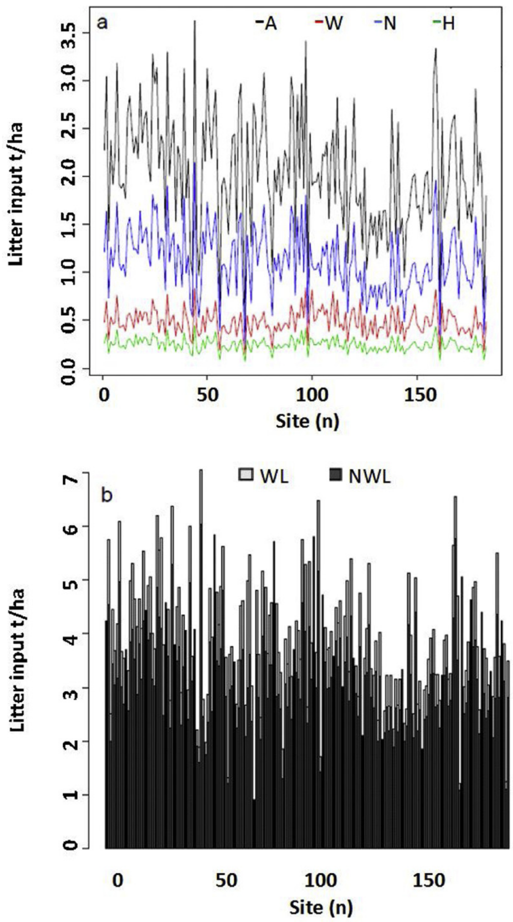

Fig. 4. Litter input at calibration sites, broken down by carbon compartments: A(dark)-W(red)-H(green)-N(blue) in Fig. 4a and non-woody litter (NWL, grey bars) and woody litter (WL, dark bars) in Fig. 4b (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

respectively, including all three carbon sources of living trees, natural mortality and harvest residue. For the model to operate, the initial state of carbon compartments must be set down. For this, the calibrated YassoBW with new parameter set was initialized from the status of zero carbon stock for the NFSI sites (sample plots). The NWL and WL inputs were taken from the measured data of the quasi-NFI survey and were differentiated for each site. The annual climate data that is required by YassoBW was also site-specific. The average over 20 years at each site was used. Then YassoBW was run for 10,000 years to obtain the new equilibrium state of soil carbon stock in the different AWENH compartments for NWL and WL, separately (details in Supplementary).

2.4.3. Model simulation

The projection was implemented for all possible combinations of storm frequencies, management strategies and three IPCC climate scenarios from the fifth assessment report. The combination of simulation runs is listed in Table 3. Firstly, storms were assumed to return at 10, 20 or 50 year intervals. After a storm event, three different post-storm harvest strategies were distinguished: business as usual (BAU), full retention (RM) and half retention-half harvest (HH). For each combination, the simulation run was repeated 40 times, to account for the stochastic model effects and the results were averaged from the 40 runs, to analyze the general soil carbon change trends and the uncertainty of model runs, as well as the variability between NFSI sample sites. The simulation was carried out for each of the NFSI sites (183 sample plots) and run for 100 years under each of 30 combinations of scenarios for each of the 43 parameter sets. In total, more than 23 million individual runs were executed, alone for the projection of YassoBW.

2.4.4. Determinants of soil carbon stock changes

Soil carbon stock projections were performed at the NFSI site level, using site-specific litter input and annual climatic data. An annual carbon stock projection for the time period 2001–2100 was obtained for each NFSI site, under all of the 30 scenarios (Table 3). Climate change affects the YassoBW projection in two ways by determining the litter input, because forest biomass increment were projected by the six climate-biomass models using temperature, precipitation and CO_2 as the independent predictors and climate data being determinant for the decomposition rates of the carbon compartments in YassoBW.

A practical indicator was used to categorize storm severity, here the percentage of storm damaged timber to total growing stock within a certain region. This percentage can be directly calculated from measured data. More importantly, this percentage can be easily transformed to litter input to soil carbon, assuming that the wood density was constant. The storm damage in our simulations destroys 10% of the total growing stock over bark as Lothar storm damage did in the region (Kändler et al., 2005). Correspondingly, the biomass damage and annual litter input will increase by the same proportion in the first year after a storm, if no post-storm harvest occurred. The effects of this event on regeneration is regarded as soon as a new stand reaches the first diameter class (10 cm). After a storm event, three post-storm harvest strategies were combined with the above mentioned three storm frequency scenarios: BAU, HH, and RM. The BAU scenario was derived from the “Lothar” damage measurements. As resulted from NFI2 about Lothar storm damage effects (Kändler et al., 2005), 95% of the total damaged biomass was removed from the affected forests, 32% of which was left as harvest residue. Half of the harvest residue is assumed to be collected as fuel wood according to the local practice, whereas the other half of the residue was considered to be the real litter input into the forest soil (as in Yasso07 in Tuomi et al., 2008, 2009). Similarly, the HH and RM scenarios assumed that 50% and 100% of the total damaged biomass were left in forests as litter input into the soil, respectively. A storm of the severity of “Lothar” was assumed to return in chronological order according to the three storm frequencies. The increased litter input from storm events declined linearly from the first year after the storm to the last year before the next storm came. Therefore, the first year had the largest litter input rise, which corresponds logically to the storm severity of 10%.

2.4.5. Forest carbon budget

To assess the influence of storm events on forest carbon budget, the above ground biomass carbon pool (derived from Eq. (3)) must be combined with the soil carbon pool. Here, the biomass carbon stands for the carbon stored in the above ground biomass and roots. The biomass in the roots was calculated by multiplying the above ground biomass with the root-shoot ratio, which was empirically derived from the quasi-NFI database. In this study, the forest carbon budget with storm and without storm scenarios was analysed. The projection was implemented at a yearly step, but the accumulated changes were illustrated for the time periods of 20, 50 and 100 years in order to capture the tendencies of change starting from the year 2000 (see details on Forest carbon modelling in Supplementary 1, section 2.4).

2.5. Validation of YassoBW

YassoBW was validated by comparing the NFSI re-measured sites information for 280 sample plots with YassoBW predicted carbon stock, either in carbon stock status or in annual carbon stock changes. YassoBW prediction started from inventory year of NFSI1 and ended at the year of NFSI2. This simulation length was emphasized because the two consecutive NFSIs were not finished within one year and the starting year of NFSI1 at each site was not the same year either. It

Table 3
Simulation scenarios to estimate soil carbon stocks in BW under different storm frequencies, management strategy and IPCC climate scenario. We apply three post storm management strategies namely business as usual (BAU), full retention (RM), and half retention (HH), respectively.

		Storm	Frequency		Management	Strategy		IPCC	Scenario	
Scenario	No Storm	10 Years	20 Years	50 Years	BAU	RM	HH	RCP26	RCP60	RCP85
1	x							x		
2	x								x	
3	x									x
4		x			x			x		
5		x			x				x	
6		x			x					x
7		x				x		x		
8		x				x			x	
9		x				x				x
10		x					x	x		
11		x					x		x	
12		x					x			x
13			x		x			x		
14			x		x				x	
15			x		x					x
16			x			x		x		
17			x			x			x	
18			x			x				x
19			x				x	x		
20			x				x		x	
21			x				x			x
22				x	x			x		
23				x	x				x	
24				x	x					x
25				x		x		x		
26				x		x			x	
27				x		x				x
28				x			x	x		
29				x			x		x	
30				x			x			x

resulted in the fact that the starting year and ending year, as well as their time difference between NFSIs were also site-specific. With the aim to make the validation more reasonable and justifiable, these site-specific features were taken into consideration. Thus, the YassoBW projection was carried out at site level to predict the carbon stock change from the year of NFSI1 to NFSI2, also using site-specific annually varying climate data. Therefore, it is meaningful and verifiable to compare the YassoBW output at the year of NFSI2 and the measured data of NFSI2. The similar comparison was also implemented for the annual carbon stock changes between YassoBW estimates and NFSI measurements.

2.6. Sensitivity and uncertainty analysis

The sensitivity of YassoBW was analyzed in relation to the two important sets of model input, e.g. climate and litter input. The sensitivity of YassoBW to climate data was examined by simulating YassoBW using either standard temperature with annually changing precipitation, or standard precipitation with annually changing temperature for the historical period of 1989 - 2008. Here, standard temperature and precipitation stand for the 20 year average at the state level. The temperature amplitude and annual litter input calculated as the mean over all NFSI sites and were held constant over 20 years (1989–2008). On the other hand, in order to detect the sensitivity of YassoBW output to litter input, the model was run with annually varying litter input and constant climate data. The annually varying litter input was derived from the biomass increase under the climate scenario RCP60. The constant climate data were calculated as the 20 year average for the 183 NFSI sites, according to the German Meteorological Service (DWD) observations. For comparison to climate sensitivity, the model was also run with constant litter input (quasi-NFI data at the state level) and annually varying climate data from the RCP60 scenario. Here, sensitivity was investigated by checking the ratio of YassoBW output changes in percentage to input changes (e.g. litter, temperature, precipitation) in percentage. This study focused mainly on the uncertainty in YassoBW parameter values and their impact on soil carbon projections. This impact was evaluated by randomly selecting 40 parameter vectors from the posterior parameter space. These different parameter vectors were used for each of the 30 simulation scenarios in this study. The uncertainty of YassoBW projections was then assessed by calculating the ranges and standard errors of 40 simulation runs for each scenario.

3. Results

3.1. Calibrated parameter values of YassoBW

The parameter values of YassoBW were actualized by selecting statistically representative samples from the posterior parameter space. The mean values and the corresponding 95% confidence intervals of all candidate points in the parameter space are shown in Table 4. These values were applied to further predictions under different scenarios in BW. Compared to the original Yasso07 parameter set, most parameters do not deviate significantly from the original parameters, in terms of numeric magnitude, but some mass flow rates among the A-W-E-N-H compartments increased or changed from zero to non-zero values. More importantly, the confidence intervals of all parameters were significantly reduced after they were calibrated using the locally measured data. To evaluate the uncertainty of the newly calibrated YassoBW parameter values, this study adopts the coefficient of variation (COV) as a criterion for uncertainty assessment. The overall average COV for all parameters was reduced by roughly 33%, whereas the reduction for each parameter varies. More specifically, the COV of the decomposition rate coefficients for A-W-E-N-H–*N-H were reduced by 30%* - 39%. The COV of mass flow rates among A-W-E-N-H 44%. Finally, the parameters for the climate dependence of the decomposition rates and woody litter

Table 4
Mean of posterior parameter values of YassoBW and their 95% confidence intervals.

Parameter	Value	Confidence Interval	Unit	Interpretation
a_1	−0.7283	1.79E-04	a^{-1}	Decomposition of A
a_2	−5.8961	1.48E-03	a^{-1}	Decomposition of W
a_3	−0.2861	7.99 E-05	a^{-1}	Decomposition of E
a_4	−0.0317	1.11 E-05	a^{-1}	Decomposition of N
p_1	0.4840	9.01 E-05	–	Mass flow rate, W to A
p_2	0.0299	1.10 E-04	–	Mass flow rate, E to A
p_3	0.8398	3.01 E-04	–	Mass flow rate, N to A
p_4	0.9857	3.91 E-05	–	Mass flow rate, A to W
p_5	0.0167	6.47 E-05	–	Mass flow rate, E to W
p_6	0.0541	1.86 E-04	–	Mass flow rate, N to W
p_7	0.0008	2.98 E-06	–	Mass flow rate, A to E
p_8	0.0008	2.82 E-06	–	Mass flow rate, W to E
p_9	0.0680	2.30 E-04	–	Mass flow rate, N to E
p_10	0.0021	8.55 E-06	–	Mass flow rate, A to N
p_11	0.0150	2.03 E-05	–	Mass flow rate, W to N
p_12	0.9357	1.42 E-04	–	Mass flow rate, E to N
b_1	0.0949	3.02 E-05	$°C^{-1}$	Temperature dependence
b_2	−0.0015	1.05 E-06	$°C^{-1}$	Temperature dependence
y_1	−1.2075	2.35 E-04	m^{-1}	Precipitation dependence
k_h	−0.0017	4.55 E-07	a^{-1}	Humus decomposition rate
p_h	0.0045	1.37 E-06	–	Mass flow to humus
q_1	−1.7085	2.57 E-04	cm^{-1}	First order size dependence
q_2	0.8580	1.52 E-04	cm^{-1}	Second order size dependence
r	−0.3063	2.17 E-05	–	Size dependence power

size dependence decreased as well, by 33%–37% in relation to the COV value.

The trace plots for all 24 parameters converged after the MCMC was run with a chain length of 10^5. An example is indicated in Fig. 5 showing the fact that none of these trace plots tends to explore a new parameter space. The posterior marginal probability distributions of the YassoBW parameters were plotted as a histogram along with the MCMC trace at the right side of the histogram (Fig. 5). Similar patterns are identified for all 24 parameters (see supplementary material, section 6). These histograms show sharply peaked distributions, which in return prove again the reduction in posterior uncertainties of the parameter values. Although the NFSI measurements might have measurement errors, they still contain sufficient information to restrain the uncertainty of predictive power, which is exactly the purpose of Bayesian calibration. Most of these marginal distributions could be fitted with normal distributions. The joint posterior distribution was therefore regarded as a multivariate normal distribution. In the next section, the 40 parameter sets were randomly generated from this multivariate normal distribution. These 40 parameter sets were used for the YassoBW projection to account for the effect of parameter uncertainties on the YassoBW outcomes.

3.2. Validation of YassoBW

The initial state of carbon stock at the beginning of model run was the real measurements from NFSI1, broken down into AWENH components for non-woody litter and woody litter. In this regard, the AWENH proportion was assumed to be the same as it is in the equilibrium state from YassoBW initialization results. The litter input varied at each sampling site, but was kept constant over the simulation years for validation. YassoBW was run at each site for the length of time difference between NFSI1 and NFSI2. This means YassoBW was not run for the same number of years for all sites. Rather, each site had its own individual simulation length, ranging from 5 to 18 years, and ran with both the annually changing climatic data and mean climate data.

YassoBW was run at each site for the duration of the time difference between NFSI1 and NFSI2 and was applied to project the soil carbon stocks at 183 NFSI sites within the six growth regions (Fig. 1). According to the measurements of NFSI up to the topmost 60 cm mineral soil in the 280 re-sampled sites, the total SOC has been reduced by 16.9% on average from NFSI1 to NFSI2. The mean of total SOC was 108.0 t/ha in NFSI1 and 89.8 t/ha in NFSI2, with a standard deviation of 160.1 t/ha and 64.0 t/ha, respectively. When the extreme values with higher than 100% standard deviation in NFSI1 were ignored, its mean value and standard deviation became 99.2 t/ha and 36.8 t/ha. Both humus horizon and mineral soil experienced carbon stock losses. The humus horizon was reduced by 4.7 t/ha and the mineral by 13.5 t/ha on average between the two soil surveys. This indicates that mineral soil played a more important role in the carbon stock reduction in absolute quantity. As shown in Table 5, the soil organic carbon stock was reduced from 16.0 t/ha to 11.3 t/ha when only Humus horizon was taken into account. Among the 280 re-measured sites, 65 of which experienced carbon stock increases in humus horizon while the rest 215 sites suffered from decline. This contributed to the 29.4% overall loss of carbon stock in the humus horizon. When the top 10 cm mineral soil was included, 83 sites showed increases in carbon stock. However, the total SOC also decreased by 7.5 t/ha on average. It is very noticeable that almost 17% of SOC was lost between the two NFSIs. To conclude, it was obvious that the forest soil carbon pool in BW was a carbon source within the time frame of the two soil surveys.

The YassoBW run with annual climate data predicted a carbon stock at the end of NFSI2 95.0 t/ha, which was averaged over 183 sites. When the time difference between the two NFSIs was taken into account, the mean carbon stock of the selected 183 sites was 97.0 t/ha (Fig. 6). On the other hand, when the overall mean climate was applied in YassoBW, the soil carbon stock was predicted to be 94.3 t/ha and 96.5 t/ha at the end of NFSI2 and within the time difference between two NFSIs, respectively. Although the temporal mean YassoBW output between the two NFSIs is slightly higher than the YassoBW output at the last year of model run, both of them fall into the range of the mean of measured data by NFSI1 and NFSI2. Moreover, the YassoBW model output shows the same tendency of carbon loss as measured carbon stock regardless of which climate data was used. The reduction magnitude predicted by YassoBW (from 100.3 t/ha to 95.0 or 94.3 t/ha) was not so large as measured in NFSIs (from 100.3 t/ha to 91.3 t/ha). This might be attributed to some extreme natural disturbance in forests in BW between the two NFSIs, like “Vivian & Wiebke” storm in 1990 and “Lothar” storm in 1999. However, the YassoBW predictions at the year of NFSI2 were within the 95% confidence interval (86.6–96.0 t/ha) of the measured carbon stock in NFSI2, no matter which climatic data was used. Overall, YassoBW is well calibrated to predict the average soil carbon evolution over time using the soil carbon stock measurements. The results from YassoBW simulation showed an annual carbon loss rate of -0.4 ± 0.2 t/ha per year, which is a lower carbon source than it was as measured, however, both measurements and simulations showcased the trend of carbon reduction over time (NSFI1 to NSFI2) in forest soils in BW (Fig. 6). The measured annual carbon stocks varied among all these sites, with the highest annual accumulation of 7.5 t/ha and the largest annual loss of 8.0 t/ha except one extreme decline site. The annual carbon stock change simulated by YassoBW was also within the lower and upper limits of the measured changes. Apart from the comparison of the average of all NFSI sites, the YassoBW prediction at the year of NFSI2 at each site was also in line with the measurements of NFSI2 (Fig. 7), where even the extreme observations in NFSI2 were very well represented by the YassoBW estimate.

3.3. Modelling results

3.3.1. Litter input

The basis of litter input is assumed to be the litter input in the year 2000 at different sites (183 sites), which is the starting year of the YassoBW projection before any storm happens. As indicated in Fig. 8, non-woody litter input is obviously higher than woody litter, regardless

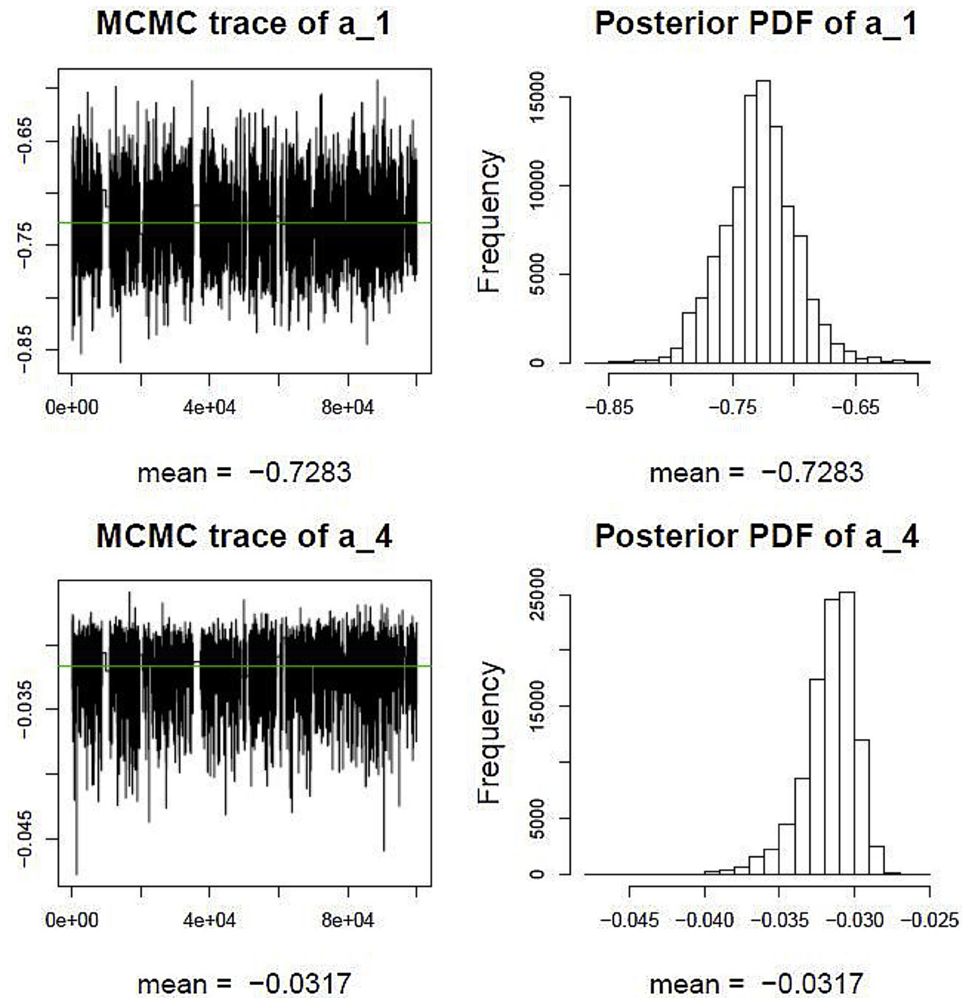

Fig. 5. Markov Chain Monte Carlo (MCMC) trace and posterior marginal probability distribution of two YassoBW parameters (a_1 and a_4). The green line indicates the mean value for each parameter (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 5
Carbon stock changes between NSFI1 and NSFI2 in 280 re-measured sites.

Horizon	NFSI1 (t/ha)	NFSI2 (t/ha)	Change in t/ha	Change in %
Humus	16.0	11.3	−4.7	−29.4
Humus + 10 cm mineral soil	47.6	40.1	−7.5	−15.8
Humus + 60 cm mineral soil	108.0	89.8	−18.2	−16.9

of the involved chemical components. Due to the differing condition at the forest sites, litter input greatly varies, except for the ethanol-solubles and water-solubles from the woody litter parts. When averaged over all the 183 NFSI sites under investigation, the quantity of A-W-E-N solubles entering the soil were 1.3 t/ha, 0.4 t/ha, 0.2 t/ha and 0.7 t/ha respectively for the non- woody litter parts and 0.5 t/ha, 001 t/ha, 0.01 t/ha and 0.3 t/ha respectively for the woody litter parts.

Without the influence of storm events, the annual litter input was only driven by the above ground biomass increase, e.g. living biomass, harvest residue and natural mortality as a fixed proportion of the above ground biomass. These percentages differed among different IPCC climate scenarios for every growth region. Storm events have an impact on litter input into the soil in different ways. The above ground biomass is reduced and the magnitude of this reduction depended on the storm severity and storm frequency. The highest increase of litter input in the first year after a storm triggered approximately 2%, 5% and 10% increase for the harvest strategies BAU, HH and RM, respectively (see supplementary 5.4 for details about litter input with and without storm effects).

3.3.2. Projection of soil carbon stock

Soil carbon stock was predicted at each NFSI site at the beginning, middle and end of this century (for 2001, 2015, and 2100) as showcased in the Fig. 9a. This figure delivers the general tendency of soil carbon stock changes for the whole forest in BW in the future at site level. When the results are further averaged over the six growth regions, the trend of SOC decline at regional level and thus state level is more clearly demonstrated in the Fig. 9b and the Table 6. The forest in the Rhine Valley region will become the least carbon stocked area in the year 2100, even though it had more SOC than Odenwald and Neckarland at the beginning of the simulation. This is mainly due to the warmer and drier climate than in other regions, which drives the speedup of decomposition rates of A-W-E-N-H component in the soil organic matters. The Black Forest and Black Forest Baar regions will still hold relativly high SOC (54.7 t/ha) in 2100, which is just less than that in the Alpine foothills region. However, this region would suffer

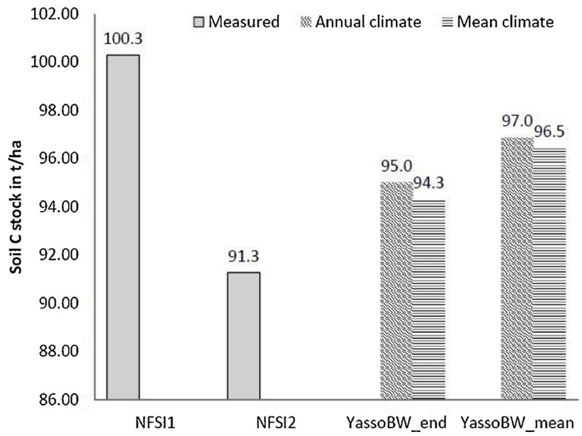

Fig. 6. The average of measured and simulated soil carbon stock of 280 remeasured sampling sites at the end of NFSI2 and average carbon stock between NFSI1 and NFSI2 using annually varying climate data for each soil survey site or long-term mean (1989–2008) climate data for all soil survey site.

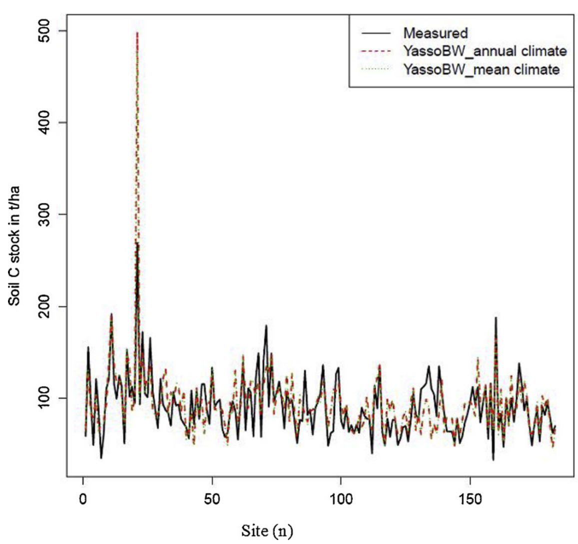

Fig. 7. Measured and simulated soil carbon stock at NFSI2 (national forest soil inventory at 2008) sites, using annual climate and long-term mean climate data.

the sharpest reduction of carbon stock quantity, leading to the release of 48 t/ha in total for the 100 year period driven by the moist soil condition. In addition, the region of Alpine foothills always has the highest soil carbon stock throughout the whole time period, although it is also losing the carbon quantity year by year. This can be attributed to milder weather conditions and the increased above ground biomass that produces more litter input into the soil in this region.

At the state level, the forest soil carbon was reduced from 92 t/ha in 2001, to 63 t/ha in 2050 and to 52 t/ha in 2100, the reduction rate having slowed down. This general reduction trend of SOC at the state level is not only displayed by the total carbon quantity but also supported by the annual carbon changes (Fig. 10). The annual SOC also decreased, but the decline range is shrinking from [-0.9, -2.3] in 2001 to [-0.1, -0.2] in 2100 based on the difference between the minimum and maximum output from the 40 simulation runs. Fig. 10 conveys two important pieces of information. Firstly, the SOC in forest area in BW decreases constantly until the end of 2100 with slowing down reduction rates. Secondly, the SOC quantity is gradually reaching an equilibrium state. The annual soil carbon change is not varying very much after 2050 and is converging towards zero regarding all complex, non-linear and interactive processes simulated by YasooBW. The range of annual SOC changes is also converging according to the simulation runs done for the proposed scenarios. This can be attributed to the trade-off effect of climate change on biomass increase and on decomposition acceleration. However, the overall average values are concealing important information, e.g., the different impact of storm frequency scenarios, post-storm management strategy scenarios and climate change scenarios as well as spatial discrepancies. The detailed influence of these different factors is analysed in the next sections.

3.3.3. Carbon stock and its annual changes under groups of scenarios

Under the “No-Storm” scenario, the soil carbon stock changes were mainly affected by annually varying litter input and the decomposition of the A-W-E-N-H. However, the soil carbon projections under three different IPCC scenarios did not differ significantly from each other, when no impact from storm events was assumed. When the mean values of the YassoBW parameters used, the projected SOC stocks at the end of the simulation were reduced to 63.0 t/ha, 62.3 t/ha and 63.0 t/ha under RCP26, RCP60 and RCP85, respectively. There was no significant difference between RCP26 and RCP85. This can be attributed to the trade-off effect between the increased above ground biomass and the accelerated decomposition rates of the chemical components A-W-E-N in the litter input. Under the RCP26 scenario, the annual litter input increment was lower than for RCP85, due to slower forest growth in the latter. Consequently, carbon loss from decomposition was also lower

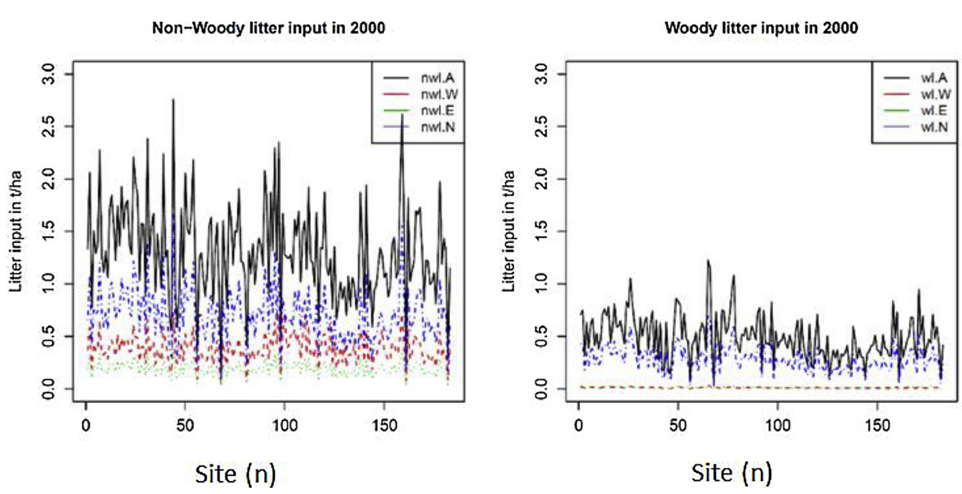

Fig. 8. Basis of non-woody litter (left) and woody litter (right) input affecting A-W-E-N solubles (labile compartments: Acid-solubles, Water-solubles, Ethanol-solubles and Non-solubles).

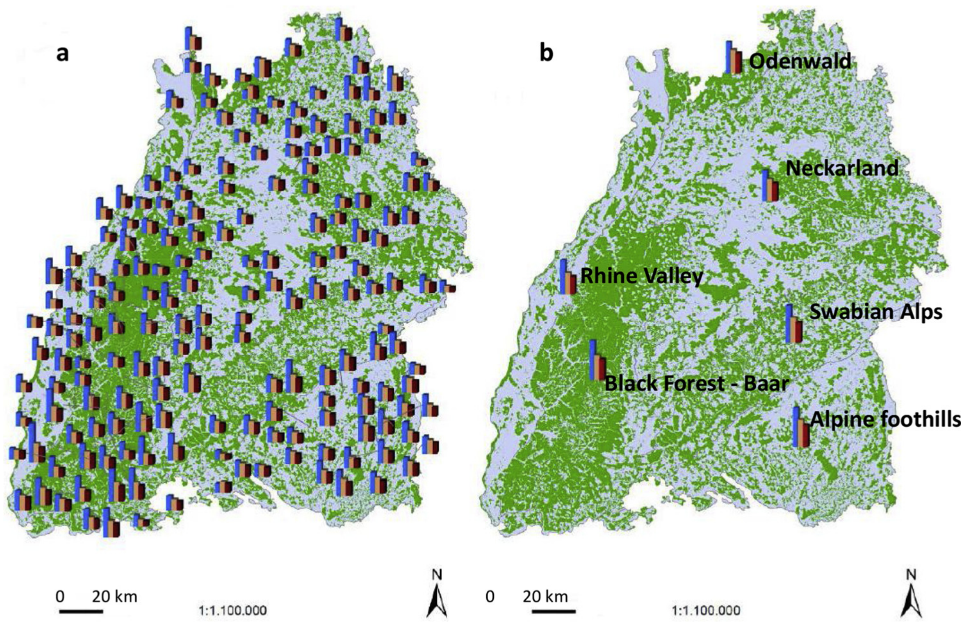

Fig. 9. Soil carbon stock status at the beginning (2001, blue bar), middle (2050, brown bar) and end of the 21 st century (2100, red bar): at NFSI site level (Fig. 9a) and at six growth regions level (Fig. 9b) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 6
Carbon stock in average for all six regions.

Region	2001	2050	2100
Rhine valley	89.1 (0.07)	56.2 (0.57)	46.5 (0.53)
Odenwald	81.7 (0.06)	61.1 (0.61)	51.6 (0.60)
BF & BF_ Baar[a]	102.8 (0.08)	65.4 (0.59)	54.7 (0.56)
Neckarland	80.9 (0.06)	58.3 (0.58)	47.6 (0.55)
Swabian Alps	96.0 (0.06)	64.3 (3.58)	51.8 (0.52)
Alpine Foothills	103.0 (0.07)	72.1 (0.67)	58.5 (0.62)

[a] Stands for Black Forest. Standard errors are in the parentheses.

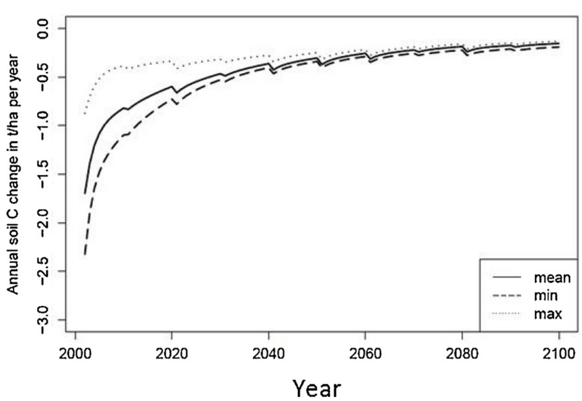

Fig. 10. Annual SOC changes throughout the 21 st century, averaged over all NFSI sites and all scenarios, distinguished by the mean, minimum and maximum changes of 40 YassoBW simulation runs.

than for RCP85, due to lower decomposition rates. In general, the decomposition-caused carbon loss exceeds the biomass increase-triggered carbon gain and thus, the overall carbon flux is negative.

Moreover, and when the spatial variation effect is not taken into account, the soil carbon stock keeps losing quantity at the state level. Among the three groups of scenarios, storm frequency is the most influential factor that drives the soil carbon changes (see figures in section 7 of Supplementary). Meanwhile, the climate and harvest strategy caused soil carbon fluctuation along with each storm frequency scenario. Under each storm frequency scenario, there are nine different combinations of climate and harvest strategy scenarios, however the harvesting scenarios caused only little soil carbon fluctuation within a storm frequency scenario. At the end of the simulation, the average of the all nine combinations were 45, 53, and 60 t/ha for the storm frequencies of 10, 20 and 50 years, respectively. A storm of the severity of “Lothar” causes more carbon loss, if it revisits the forest more frequently. More specifically, a 2.5-time increase in storm frequency caused an additional loss of C of around 8% and a frequency five times higher led to an additional loss of around 16% compared to the lowest frequency. On the other hand, the annual SOC changes also displayed an apparent drop in every 10, 20 and 50 years, due to storm-damaged above ground biomass, which is consistent with the storm frequency scenarios. Similarly, when the output from nine scenario combinations under each storm frequency scenario was averaged, the annual mean SOC changes for the entire simulation period were -0.3, -0.4, and -0.5 t/ha under the Lothar50, Lothar20 and Lothar10 scenarios, respectively (see details on the sensitovoty of the SOC changes to underlying climate, storm, and harvest scenarios in supplementary material section 2.5). Moreover, there were substantial differences among study regions and their annual SOC changes (See details in Supplementary 2.6 and 7).

3.3.4. Annual changes in regional soil organic carbon (SOC)

Changes in annual SOC accumulates in the 21st century and finally reduces the total SOC at the end of century compared to the reference year 2001. Fig. 11 shows SOC reduction quantities under three storm and one no storm scenarios. To highlight the influence of different storm frequencies alone on the soil organic carbon changes, the predicted changes include one fixed harvest strategy (full retention of the destroyed timber) and one IPCC climate scenario (RCP60).The average of the total SOC of the soil survey sites within each varied from 46.5 t/ha in the region “Rhine Valley” to 58.5 t/ha in the region “Alpine Foothills”, while the total SOC at each site level showed a larger range. The more frequent storm scenario “Lothar10” decreases the total SOC to a highest amount 39–57 ton/ha in all regions. The decline triggered by a 10-year or 20-year storm frequency was 48% or 22% higher than that of a 50-year storm frequency, respectively. In the extreme case of the region “Odenwald”, the reduction of a Lothar10 scenario was over 75% higher than that of a Lothar50 scenario. Furthermore, the SOC reduction in the “Black Forest and Black Forest Baar” region was the highest, with at least 40 t/ha within 100 years, while “Odenwald” and

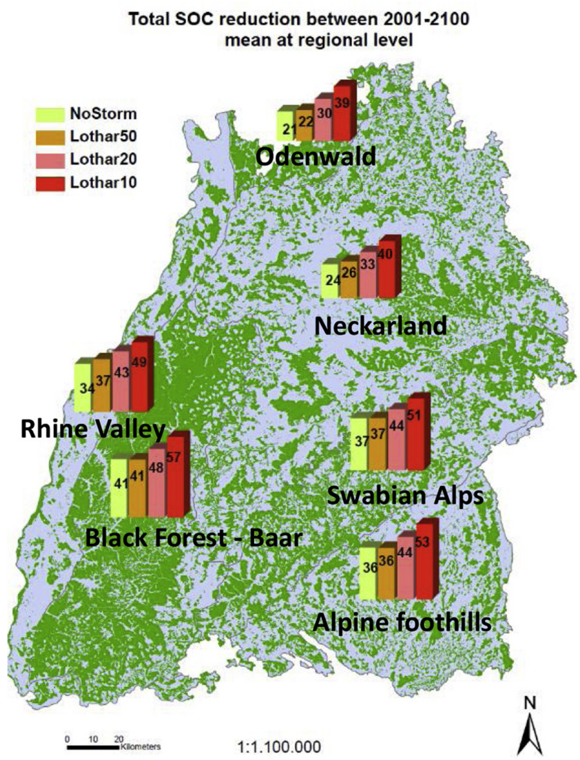

Fig. 11. Total SOC reduction between 2001–2100 in t/ha applying IPCC climate scenario RCP60.

“Neckarland” lost soil carbon stock at a relatively slower rate than “Black Forest and Black Forest Baar” with below 40 t/ha. Figures are very close for the no storm and Lothar50 scenario, however, lothar50 realizes a slightly higher total SOC reduction.

4. Discussion

4.1. Bayesian calibration of YassoBW

According to Häkkinen et al. (2011), the comparison on a plot-scale with litter inputs produced from the measurements on these plots can be highly uncertain. Bayesian calibration has strongly contributed to reducing the uncertainty of YassoBW parameter values (e.g., average coefficient of variation (COV) reduced by around 30%. van Oijen et al (2013) assessed the six forest models using the data of Scots pine across four European countries: Austria, Belgium, Estonia and Finland and concluded that the parameter uncertainty in five of the six models were reduced and the averaged reduction ranged from 1%–13% in terms of standard deviation of marginal parameter distribution.

4.2. Storm and carbon stock change

According to the result of the present study, storm frequency is the most influential factor determining soil carbon sequestration capacity. It was found that with the increase in frequency of storms with the severity of “Lothar” from 50, 20 to 10 years, the annual SOC loss was accordingly increased by 21% and 46%. However, there are few studies comparing the different impacts of various storm frequencies. A similar study in Switzerland using the old version of the Yasso model concluded that the increased storm frequency (from 15 to 10 years) only had a small impact on carbon sequestration in forests on the national scale (Thörig et al., 2005). This is probably attributed to two major reasons: firstly, the intensity of frequency increase in the present study was much higher than that assumed in the Swiss study; secondly, an extreme devastating storm “Lothar” was taken as the reference storm event, which caused more damages to BW than the storm damages to the Switzerland at national level.

4.3. Effects of management on carbon stock change

Different post-storm harvest strategies affect the soil carbon projection by extra litter input induced by storms. Based on the forest practice in BW, the business-as-usual (BAU) scenario brings least extra litter input into the soil, followed by the “half retention” (HH) scenario, and the “full retention” (RM) scenario introduces the most extra litter input. Accordingly, the projected soil carbon stock under the three scenarios followed the same order, but the absolute differences between the three harvest strategies were not significant. The largest difference in annual SOC losses between the BAU and RM scenario was only 0.005 t/ha per year (for details see section 3.2.3.3). This is in agreement with the finding of the study by Thürig et al. (2005), which stated that the post-storm harvest strategy was distinguished as “clearing” (comparable to BAU scenario in my study) and “no-clearing” (comparable to RM scenario in my study), and concluded that the “no-clearing” scenario produced only a slightly more positive carbon budget than the “clearing” scenario at national level. Furthermore, the overall impact of harvesting (e.g. the biggest difference between “total retention” and “total remove” scenario) on soil carbon change was limited to a reduction of -2%. This impact is much less than the finding of the study by Nave et al. (2010). They found that a significant reduction (-8%) for both forest floor and mineral soil resulted from forest harvesting, based on their extensive review on 432 studies dealing with soil carbon response to harvest in temperate forests around the world.The forest floor was more vulnerable to harvest-induced loss (-30%) than mineral soil with no significant change (Nave et al., 2010). In addition, if the storm-damaged trees are not removed from the forest, the projected SOC would be very comparable to output from “No-Storm” scenario under the same climate scenario, as storms not only trigger extra litter input but also destroy above ground biomass, which is the major source of litter input at the same time. More specifically, storm-induced extra litter input can be almost totally offset by the reduced litter input from above ground biomass that is damaged by that storm. Interaction between the impact of disturbance on forest carbon stock and forest management strategies (e.g., rotation period, thinning regime, and forest structure and species composition) have widely been addressed (Seidl et al., 2014; Le Page et al., 2013; Metsaranta et al., 2011).

4.4. Effects of climate on carbon stock change

YassoBW is more sensitive to variations in precipitation than to variations in temperature. This result is in line with the finding by Rantakari et al. (2012). It is more obviously illustrated by the relative changes of SOC to climate changes. However, the decomposition rates are affected by temperature and precipitation simultaneously. Taking the fixed temperature and precipitation during the simulation into account, the joint turning points for temperature and precipitation shall lie in the range of 6 °C–8 °C and 600 mm – 800 mm. Most regions in BW have higher temperature and more precipitation than this range when climate change scenarios are adopted and the YassoBW projection at the state level indicates carbon loss in forest soil. This inference is only based on the carbon stock projection using only climate driver alone. Actually, YassoBW output relies not only on climate-induced decomposition, but also annual litter inputs that are changing with climate condition.

We fitted six climate-biomass models using retrospective temperature, precipitation and CO2 concentration data. These models have obvious drawbacks because they do not include any dendrometric and site condition variables as predictors. According to Tuomi et al. (2009), the decomposition rate factor is mainly controlled by the annual mean temperature and annual precipitation in a non-linear way. In BW, the annual precipitation under various IPCC climate scenarios does not

differ strongly in the six growth regions, so that the decomposition rates do not show large regional differences. In addition, the magnitude of annual precipitation in BW is around 1000 mm, which is much higher than the threshold value of 550 mm (Rantakari et al., 2012) that turns forest soil from a sink to a source. This partly explains why the soil carbon stock projections of YassoBW keep a similar decline tendency in all growth regions in BW. Härkönen et al. (2011) pointed out that when a process-based model is applied to estimation of carbon fluxes for a large region, Yasso07 likely relies too much on climate data, in particular precipitation. So, it is necessary to be aware of the uncertainty of YassoBW outputs, especially due to climate-driven changes.

Zell et al. (2009) used a mixed nonlinear decay model following a complex exponential formula and applied not only climatic data but also tree species and diameter as predictors to predict decay rates of coarse woody debris. They concluded that temperature had a positive effect on decay rate and the optimal annual precipitation for maximum decay rate was between 1100–1300 mm.

Obviously, different model structures and equations result in various degrees of climate dependence of decomposition rates. It is also important to point out that some studies did not even include climatic data as independent variables in their decomposition analysis, regardless of which type of equation was adopted, e.g. logarithmic form in Naesset (1999), double exponential equation in Berg et al. (1991) and sigmoidal function in Laiho and Prescott (1999). Therefore, in order to better reflect the impact of climate on soil carbon stock changes, it is necessary to develop a local climate dependence model for the analysis of decomposition rates or to modify the above formula structure and compare it with other decomposition formulas, which is beyond the research scope of this study, but could be an interesting topic in future studies.

Based on this simulation, the general trend of the CO_2 effect on biomass development is clearly visible, but it is not straightforward how this is going to affect the carbon sequestration capacity, as the real forest soil carbon stock changes rely heavily on storm events, decomposition rates and harvest strategies. On the other hand, it is widely studied that the CO_2 fertilization effect might not be true for all regions and all tree species (Reyer et al., 2010). The positive response will probably be outweighed by negative effects caused by extreme climate and disturbances, e.g. storm, drought, fire and insect risks (Hanewinkel et al., 2014; Reyer et al., 2017), especially in southern and Eastern Europe (Lindner et al., 2010). Therefore, this study adopted a relatively conservative estimation (through logarithm represented in sections 2.4.2 and 2.4.4) of biomass increase due to increasing CO_2 concentration.

4.5. Soil carbon

To date, very few studies have addressed the issue of forest soil carbon stock change in each individual compartment A-W-E-N-H referring to acid-solubles (A), water solubles (W), Eethanol solubles (E), non-solubles (N), and one recalcitrant humus compartment (H) in YassoBW. We found that the largest reduction from the loss in non-solubles A-W-E-N-H were produced under the selected RCP60 climate scenario in BW. Under a similar scenario in Slovenia, Kobal et al. (2015) also found that non-solubles contributed most to the total soil carbon reduction in their case study region, but at a much lower magnitude than our result. This can be partly attributed to the inclusion of storm damage in our simulation. On the other hand, the relative decrease was found to be similar among the compartments A-W-E-N with around 60% decline for the 100 years of simulation in our study, while in the Kobal et al. (2015) study, the relative decrease of the four compartments varied under different climate scenarios with an average of around 30%. Moreover, both studies concluded that humus (H) compartment was the most recalcitrant component in the long-term simulation.

The reduction in soil organic carbon (SOC) is the result of many complex and interactive factors. Historically, it can be attributed to both anthropogenic reasons, e.g. forest practice, and natural influences, e.g. climatic situation in BW. Increase in temperature and precipitation are the most influential drivers of carbon loss. Along with temperature and precipitation increases, decomposition rates of all carbon compartments rose as well, which lead to a release of carbon from the soil to the atmosphere. Apart from that, changes in forest management also contributed to soil carbon loss. First of all, the change of the silvicultural strategy, with the transformation from coniferous to broadleaved forests, which grow slower and have lower turnover rates, led to reduced litter inputs. Second, forest stands are less dense than in the past, due to different thinning regimes (mostly thinning from below in the recent years). Both of the forest practices contributed to decreased litter inputs. In addition, according to the crown condition survey in BW (Meining et al., 2007), a reduction of the foliage was observed, that may have also lead to reduced litter input. YassoBW projected a declining tendency until 2100. However, YassoBW might systematically underestimate the SOC in BW, because understory vegetation and its contribution to litter input was not included in the study and soil carbon pools were restricted to the humus horizon and the top most 60 cm of the mineral soil. Moreover, YassoBW does not simulate carbon movement in soil layers e.g. natural movement of carbon to down profile or due to different ploughing depths.

5. Conclusion

In general, we were able to successfully calibrate and validate the model YassoBW to the forest conditions in Southwest Germany and use it to predict soil carbon stocks and stock changes on the regional level. We recognized Bayesian calibration as a reliable and practical approach to calibrate a complex process-based dynamic model, like YassoBW. It can significantly reduce the uncertainty in parameter values, especially when the locally measured data that are used for the calibration have small measurement errors. Although the uncertainty in YassoBW parameter values have been further reduced by applying Bayesian calibration approach, this is still one of major factors contributing to the uncertainty in YassoBW projections. Apart from that, YassoBW projections are also associated with uncertainties in two additional aspects: decomposition rates and litter input. In order to compare the accuracy of YassoBW projections, it is recommended to simulate the soil carbon dynamic in BW using other soil carbon models through the method of Bayesian Model Comparison in future studies.

According to the YassoBW simulation, soil carbon will continue to decline until the end of this century, no matter which combination of scenarios will be used. This general decline tendency is mainly driven by fast decomposition rates of chemical components A-W-E-N-H in the soil. Based on the decomposition formula applied in this study, the carbon loss due to decomposition cannot be compensated by litter input from biomass growth and thus leads to a reduction in soil organic carbon. Based on the analysis of climate dependency of YassoBW, it can be concluded that forest soil in BW will be a carbon source for quite a long term under current climate conditions using the present decomposition equation, although at the NFSI sampling site level, some sites also accumulate soil carbon due to large litter input and lower temperature and less precipitation.

Assessing the impact of three scenario groups of IPCC climate, storm frequency and harvest strategy on soil carbon stocks, storm frequency was found to be the most influential factor determining soil carbon sequestration capacity. Second of all, post-storm harvest strategy is the least important determinant. The overall impact of harvesting (e.g. the biggest difference between “total retention” and “total remove” scenario) on soil carbon change was limited to a reduction of -2%. This implies that future policies shall focus on the integrated impact of forest management strategies on soil carbon changes, in order to mitigate the overall impact of storm events on forest carbon budget. Third, IPCC climate scenarios are more influential than harvest strategies and less

influential than storm frequencies. Most carbon loss is observed in RCP85 scenario, whereas the least in the RCP26 scenario.

The largest reduction of forest soil carbon stock in BW originated from the loss in non-solubles (N), followed by acid-solubles (A), humus (H), water-solubles (W) and ethanol-solubles (E). Moreover, the reduction of carbon stock in each compartment is influenced by several factors, e.g., initial carbon status, decomposition rate, mass flows between compartments and annual supply from litter input. Moreover, YassoBW is more sensitive to climate variables than to litter input. Furthermore, annually changing precipitation is a more sensitive variable than annual temperature. The total forest carbon budget is affected by integrated impacts of both biomass carbon and soil carbon, and the soil carbon stock change is more influential in determining the total forest carbon budget than the biomass carbon change in BW. The storm event has a larger impact on biomass carbon than the soil carbon pool, since different post-storm harvest scenarios do not significantly change the soil carbon stocks. Moreover, the occurrence of storm events will not change the situation of forest as a negative carbon budget, but will further enlarge the reduction in forest carbon stocks to different degrees, according to different storm frequency and climate scenarios.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecolmodel.2019.02.019.

References

Bellassen, V., Luyssaert, S., 2014. Carbon sequestration: managing forests in uncertain times. Nature 506, 153–155.

Berg, B., et al., 1991. Data on needle litter decomposition and soil climate as well as site characteristics for some coniferous forest sites, part II, decomposition data. Report 42 (Swedish University of Agricultural Science).

Blennow, K., Sallnäs, O., 2004. WINDA - a system of models for assessing the probability of wind damage to forest stands within a landscape. Ecol. Modell. 175, 87–99.

BMELV, 2007. Ergebnisse der Waldzustandserhebung 2007. 31 pp. Bundesministerium für Ernährung, Landwirtschaft und Verbraucherschutz).

Friedlingstein, P., et al., 2006. Climate-carbon cycle feedback analysis: results from the C4MIP model intercomparison. J. Clim. 19, 3337–3353.

FVA, 2011. (Forest Researcjh Instute of Baden Württemebrg), 2011. Waldzustandsbericht. http://www.fva-bw.de/publikationen/wzb/ws2011.pdf.

Gardiner, B., Blennow, K., Carnus, J., Fleischer, P., 2011. Destructive Storms in European Forests: Past and Forthcoming Impacts. Final report to European Commission (DG Environment).

Goodale, C.L., et al., 2002. Forest carbon sinks in the Northern Hemisphere. Ecol. Appl. 2, 891–899.

Häkkinen, M., Heikkinen, J., Mäkipää, R., 2011. Soil carbon stock increases in the organic layer of boreal middle-aged stands. Biogeoscience 8, 1279–1289.

Hanewinkel, M., Kuhn, T., Bugmann, H., Lanz, A., Brang, P., 2014. Vulnerability of uneven-aged forests to storm damage. Forestry 87, 525–534.

Härkönen, S., Lehtonen, A., Eerikäinen, K., Peltomaa, M., Mäkelä, A., 2011. Estimating forest carbon fluxes for large regions based on process-based modelling, NFI data and Landsat satellite images. For. Ecol. Manage. 262, 2364–2377.

Hijmans, R., Cameron, S., Parra, J., 2014. WorldClim - Global Climate Data: Free Climate Data for Ecological Modeling and GIS. http://www.worldclim.org).

Houghton, R.A., et al., 2012. Carbon emissions from land use and land-cover change. Biogeosciences 9, 5125–5142.

IPCC, 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I (Forth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

IPCC, 2013. Climate Change 2013: The Physical Science Basis: Contribution of Working Group I (Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Jobbagy, E.G., Jackson, R.B., 2000. Vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol. Appl. 10, 423–436.

Kändler, G., Bösch, B., 2013. Methodenentwicklung für die 3.Bundeswaldinventur: Modul 3 Überprüfung und Neukonzeption einer Biomassefunktion: Abschlussbericht Version 2b. FVA-BW, Freiburg, Germany.

Kändler, G., Bösch, B., Schmidt, M., 2005. Wesentliche Ergebnisse der zweiten Bundeswaldinventur in Baden-Württemberg - Rückblick und Ausblick. For. Holz. 60, 45–49.

Kobal, M., Grčman, H., Zupan, M., Levanič, T., Simončič, P., Kadunc, A., 2015. Influence of soil properties on silver fir (Abies alba Mill.) growth in the Dinaric Mountains. For. Ecol. Manage. 337, 77–87.

Kronauer, H., 2000. Schwere Sturmschäden in Baden-Württemberg - Lothar stellt Wiebke in den Schatten. AFZ-Der Wald 55, 92–93.

Kühnel, I., 1994. Dokumentation der Sturmschäden 1990. Verschiedene Autoren. Schriftenreihe der Landesforstverwaltung Baden-Württemberg (Band 75).

Laiho, R., Prescott, C.E., 1999. The contribution of coarse woody debris to carbon, nitrogen, and phosphorus cycles in three Rocky Mountain coniferous forests. Can. J. For. Res. 29, 1592–1603.

Le Page, Y., et al., 2013. Sensitivity of climate mitigation strategies to natural disturbances. Environ. Res. Lett. 8, 015018.

Li, C., Aber, J., Stange, F., Butterbach-Bahl, K., Papen, H., 2000. A process-oriented model of N2O and NO emissions from forest soils: 1.MOdel development. J. Geophys. Res. Atmos. 105, 4369–4384.

Lindner, M., et al., 2010. Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. For. Ecol. Manage. 259, 698–709.

Liski, J., Palosuo, T., Peltoniemi, M., Sievänen, R., 2005. Carbon and decomposition model Yasso for forest soils. Ecol. Modell. 189, 168–182.

Liski, J., Tuomi, M., Palosuo, T., 2008. Yasso07-soil Carbon Model. Available at. www.environment.fi/syke/yasso.

LUBW, 2012. Climate Change in Baden-Württemberg. www.lubw.baden-wuerttemberg.de.

McNulty, S.G., 2002. Hurricane impacts on US forest carbon sequestration. Environ. Pollut. 116 (Suppl 1), S17–24.

Meining, S., von Wilpert, K., Puhlmann, H., Schröter, H., Delb, H., Petercord, R., 2007. Waldzustandsbericht 2007 für Baden-Württemberg. FVA Baden-Württemberg).

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., 1953. Equation of state calculation by fast computing machines. J. Chem. Phys. 21, 1087–1092.

Metsaranta, J., Dymond, C.C., Kurz, W.A., Spittlehouse, D.L., 2011. Uncertainty of 21st century growing stocks and GHG balance of forests in British Columbia, Canada resulting from potential climate change impacts on ecosystem processes. For. Ecol. Manage. 262, 827–837.

Muukkonen, P., Mäkipää, R., 2006. Empirical biomass models of understory vegetation in boreal forests according to stand and site attributes. Boreal Environ. Res. 11, 355–369.

Muukkonen, P., Mäkipää, R., Laiho, R., Minkkinen, K., Vasander, H., Finer, L., 2006. Relationship between biomass and percentage cover in understorey vegetation of boreal coniferous forests. Silva Fenn. 40, 231–245.

Nabuurs, G.J., Lindner, M., Verkerk, P.J., Gunia, K., Grassi, G., Michalak, R., Deda, P., 2013. First signs of carbon sink saturation in European forest biomass. Nat. Clim. Change 3, 792–796.

Nave, L.E., Vance, E.D., Swanston, C.W., Curtis, P.S., 2010. Harvest impacts on soil carbon storage in temperate forests. For. Ecol. Manage. 259, 857–866.

Parton, W., Schimel, D., Cole, D., Ojima, D., 1987. Analysis of factors controlling soil organic matter levels in Great Plains grasslands. Soil Sci. Soc. Am. J. 51, 1173–1179.

Parton, W., Ojima, D., Cole, C., Schimel, D., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: Bryant, R.B., Arnold, R.W. (Eds.), Quantitative Modeling of Soil Forming Processes; Soil Science Society of America. Special Publication, Madison and USA.

Patenaude, G., Milne, R., van Oijen, M., Rowland, C.S., Hill, R.A., 2008. Integrating remote sensing datasets into ecological modelling: a Bayesian approach. Int. J. Remote Sens. 29, 1295–1315.

Peltola, H., Kellomäki, S., Vaisanen, H., Ikonen, V.P., 1999. A mechanistic model for assessing the risk of wind and snow damage to single trees and stands of Scots pine, Norway spruce and birch. Can. J. For. Res. 29, 647–661.

Rantakari, M., Lehtonen, A., Linkosalo, T., Tuomi, M., Tamminen, P., Heikkinen, J., Liski, J., Mäkipää, R., Ilvesniemi, H., Sievänen, R., 2012. The Yasso07 soil carbon model – testing against repeated soil carbon inventory. For. Ecol. Manage. 286, 137–147.

Reyer, C.P.O., Gutsch, M., Lasch, P., 2010. Meta-analysis of simulated forest productivity changes under global change. Geophys. Res. Abs. 13 (EGU2011-2473, 2011).

Reyer, C.P.O., Bathgate, S., Blennow, K., Borges, J.B., Bugmann, H., Delzon, S., Faias, S.P., Garcia-Gonzalo, J., Gardiner, B., Gonzalez-Olabarria, J.R., Gracia, C., Guerra Hernández, J., Kellomäki, S., Kramer, K., Lexer, M.J., Lindner, M., van der Maaten, E., Maroschek, M., Muys, B., Nicoll, B., Palahi, M., Palma, J.H.N., Paulo, J.A., Peltola, H., Pukkala, T., Rammer, W., Ray, D., Sabaté, S., Schelhaas, M.J., Seidl, R., Temperli, C., Tomé, M., Yousefpour, R., Zimmermann, N.E., Hanewinkel, M., 2017. Are forest disturbances amplifying or canceling out climate change-induced productivity changes in European forests? Environ. Res. Lett. 12 (034027). https://doi.org/10.1088/1748-9326/aa5ef1.

Rottmann, M., 1986. Wind- und Sturmschäden im Wald. (Sauerländer, Frankfurt).

Schelhaas, M.J., Nabuurs, G.J., Schuck, A., 2003. Natural disturbances in the European forests in the 19th and 20th centuries. Glob. Change Biol. 9, 1620–1633.

Schelhaas, M.J., Kramer, K., Peltola, H., van der Werf, D.C., Wijdeven, S.M.J., 2007. Introducing tree interactions in wind damage simulation. Ecol. Model. 7, 197–209.

Schmidt, M., Hanewinkel, M., Kändler, G., Kublin, E., Kohnle, U., 2010. An inventory-based approach for modeling single-tree storm damage — experiences with the winter storm of 1999 in southwestern Germany. Can. J. For. Res. 40, 1636–1652.

Seidl, R., Schelhaas, M.J., Rammer, W., Verkerk, P.J., 2014. Increasing forest disturbances

in Europe and their impact on carbon storage. Nat. Clim. Change 4 930-930.
Stange, F., Butterbach-Bahl, K., Papen, H., Zechmeister-Boltenstern, S., Li, C., Aber, J., 2000. A process-oriented model of N2O and NO emissions from forest soils. 2. Sensitivity analysis and validation. J. Geophys. Res. Atmos. 105, 4385–4398.
Talkkaria, A., Peltolab, H., Kellomaeki, S., Strandman, H., 2000. Integration of component models from the tree, stand and regional levels to assess the risk of wind damage at forest margins. For. Ecol. Manage. 135, 303–313.
Thürig, E., Palosuo, T., Bucher, J., Kaufmann, E., 2005. The impact of windthrow on carbon sequestration in Switzerland: a model-based assessment. For. Ecol. Manage. 210, 337–350.
Tuomi, M., Vanhala, P., Karhu, K., Fritze, H., Liski, J., 2008. Heterotrophic soil respiration— comparison of different models describing its temperature dependence. Ecol. Modell. 211, 182–190.
Tuomi, M., Thum, T., Järvinen, H., Fronzek, S., Berg, B., Harmon, M., Trofymow, J., Sevanto, S., Liski, J., 2009. Leaf litter decomposition - estimates of global variability based on Yasso07 model. Ecol. Modell. 220, 3362–3371.
Tuomi, M., Rasinmäki, J., Repo, A., Vanhala, P., Liski, J., 2011. Soil carbon model Yasso07 graphical user interface. Environ. Model. Softw. 26, 1358–1362.
UNFCCC, 1998. Kyoto Protocol to the United Nations Framework Convention on Climate Change. UN Pubs 1998.
van Oijen, M., 2008. Bayesian Calibration (BC) and Bayesian Model Comparison (BMC) of processbased models: theory, implementation and guidelines. Nat. Environ. Res. Council (Centre for Ecology & Hydrology).
van Oijen, M., Rougier, J., Smith, R., 2005. Bayesian calibration of process-based forest models: bridging the gap between models and data. Tree Physiol. 25, 915–927.
van Oijen, et al., 2013. Bayesian calibration, comparison and averaging of six forest models, using data from Scots pine stands across Europe. For. Ecol. Manage. 289, 255–268.
Wutzler, T., Wirth, C., Schmacher, J., 2008. Generic biomass functions for Common beech (*Fagus sylvatica* L.) in Central Europe - predictions and components of uncertainty. Can. J. For. Res. 38, 1661–1675.
Xenakis, G., Duncan, R., Mencuccini, M., 2008. Sensitivity and uncertainty analysis from a coupled 3-PG and soil organic matter decomposition model. Ecol. Modell. 219, 1–16.
Zell, J., Kändler, G., Hanewinkel, M., 2009. Predicting constant decay rates of coarse woody debris—a meta-analysis approach with a mixed model. Ecol. Modell. 220, 904–912.